Neurobiology of Learning and Memory 222 (2025) 108092

Contents lists available at ScienceDirect

Neurobiology of Learning and Memory

journal homepage: www.elsevier.com/locate/ynlme

Modelling Pavlovian biases in depressed and healthy young adults☆

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ABSTRACT

Pavlovian stimuli signalling potential punishment and reward have powerful effects on instrumental behaviours. For example, a cue associated with punishment will suppress well-learned instrumental responses. However, the degree to which Pavlovian stimuli interfere with the *learning* of instrumental responses is less well studied. In the current set of studies we investigated the effect of Pavlovian stimuli on instrumental learning and the extent to which depressive symptomatology moderated this relationship. We conducted two experiments using a sample of healthy adults and leveraged computational modelling to estimate learning parameters and the moderating role of depression on these learning parameters. In line with previous literature, participants found it more difficult to learn to make instrumental go and no-go responses in the presence of incongruent cues—for instance, making a "go" response for a cue which signalled punishment, and vice versa. Contrary to expectation we did not observe a reliable relationship between performance and depression scores; while Experiment 1 observed a relationship between depression and model-derived learning rates, these results were not replicated in Experiment 2. We discuss both the theoretical and practical implications of these findings in the General Discussion.

1. Introduction

People with depression tend to exhibit increased focus toward negative information in the environment and diminished attention towards anticipated rewards (Gotlib and Joormann, 2010; Keren et al., 2018; Kircanski et al., 2012; LeMoult & Gotlib, 2019); a type of behaviour which may arise as a consequence of the general anhedonia which defines depression. These cognitive biases (a sensitivity towards punishment and insensitivity to reward) have also been reported in the lab using reinforcement learning paradigms where patterns of learning and behavioural responses to rewards and punishments are compared between depressive and non-depressive samples (see for reviews: Chen et al., 2015; Pike & Robinson, 2022).

Reinforcement learning in depression is usually studied via simple probabilistic tasks where participants learn the reward structure of an environment by trial and error: for example, choosing between two different stimuli, and adjusting future behaviour as a result of positive and negative feedback (Brown et al., 2021; Cavanagh et al., 2019; Chase et al., 2010; Dombrovski et al., 2015; Huys et al., 2013; Rothkirch et al., 2017; Vandendriessche et al., 2023). In general, studies using these tasks have reported that individuals with depression struggle to select the optimal response following negative feedback, in line with theoretical models hypothesizing hypersensitivity to punishment (see for reviews: Chen et al., 2015; Pike & Robinson, 2022). However, the biasing effect of Pavlovian stimuli—which signal reward and punishment—are often ignored in such designs despite being an integral feature of any instrumental learning context (Dayan & Balleine, 2002; Rescorla, 1991; Rescorla & Solomon, 1967). Specifically, the Pavlovian properties inherent to any instrumental stimulus can have powerful effects on behaviour—either facilitating or conflicting with ongoing instrumental responses (Dayan & Balleine, 2002; Guitart-Masip et al., 2014).

Pavlovian stimuli that have previously been associated with reward tend to invigorate instrumental responding, whereas stimuli associated with punishment tend to suppress instrumental responding (Campese et al., 2013; Lewis et al., 2013; Prévost et al., 2012; see for reviews: Campese, 2021; Cartoni et al., 2016). This 'general Pavlovian to instrumental transfer' (general PIT) effect has been extensively studied in both humans and animals and the associated neurobiology is well characterised (Corbit & Balleine, 2005, 2011, 2016; Talmi et al., 2008; Watson & Mahlberg, 2023). In a standard PIT paradigm, the instrumental and Pavlovian learning phases are conducted separately and their interaction is studied at test, after learning. This is achieved by presenting Pavlovian stimuli while the subject is carrying out previously learned instrumental actions. Relative to a baseline period where no

☆ This article is part of a special issue entitled: 'Mechanisms of punishment' published in Neurobiology of Learning and Memory.

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https://doi.org/10.1016/j.nlm.2025.108092
Received 21 March 2025; Received in revised form 30 July 2025; Accepted 31 August 2025
Available online 7 September 2025
1074-7427/

Pavlovian stimuli are present, the general effects of the Pavlovian cues on response vigour can be assessed (see for review: Holmes et al., 2010). Typically, Pavlovian cues previously associated with reward increase instrumental response rates, whereas cues previously associated with punishment suppress instrumental responding.

A few studies have used this PIT paradigm to examine whether individuals with symptoms of depression differ in the degree to which Pavlovian stimuli invigorate or suppress instrumental behaviour (Huys et al., 2016; Metts et al., 2022; Nord et al., 2018; see for review: Garbusow et al., 2022). Of these studies, only Nord et al. (2018) found that—as expected by theoretical models which propose a bias towards negative information in depressed individuals (Gotlib & Joormann, 2010; Keren et al., 2018; Kircanski et al., 2012; LeMoult & Gotlib, 2019)—people with unmedicated major depressive disorder (MDD) showed exaggerated inhibition of instrumental responding in the presence of Pavlovian cues previously associated with punishment. In addition, depression symptomology correlated with increased inhibition of instrumental responding by punishment-related Pavlovian stimuli across conditions. By contrast, however, Huys et al (2016) and Metts et al (2022) did not observe convincing differences between a medicated MDD group and a student sample; although Metts et al. only examined reward-associated and not punishment-related Pavlovian stimuli.

While the PIT paradigm assesses the effect of Pavlovian stimuli on instrumental action *after* learning in order to isolate the transfer effect, in natural environments Pavlovian cues and instrumental actions are often learned simultaneously. For example, the coffee machine (a Pavlovian cue) signals reward, which in turn supports the instrumental action of making coffee. The cue (i.e., the coffee machine) is inherent to the instrumental learning context and is present from the beginning. It is therefore important to consider how Pavlovian and instrumental learning may interact during the learning process to more accurately reflect how these systems operate together in daily life. Moreover, it allows us to better understand how cognitive biases in depression towards punishment (and away from reward) may influence learning about novel contexts and actions.

To this end, we used the cued go/no-go task (Albrecht et al., 2016; Cavanagh et al., 2013; Guitart-Masip et al., 2012) to examine Pavlovian biases during learning. The cued go/no-go paradigm exploits the fact that expectations of reward tend to invigorate instrumental responding, and expectations of punishment tend to inhibit actions, by carefully manipulating the type of instrumental response required—either 'go' or 'no-go'. The discriminative stimulus (signalling the correct instrumental response) also acquires Pavlovian properties as it signals either reward or punishment. The acquired Pavlovian properties can therefore have either facilitatory or inhibitory effects on instrumental learning. For example, when the correct instrumental response is no-go and the stimulus has been previously associated with punishment, participants learn quickly not to respond. However, if a stimulus is associated with reward yet requires a 'no-go' response to obtain it, the incongruence between the Pavlovian approach response (go) and the instrumental response (no-go) can impede learning.

Several studies using this task have shown that healthy individuals (and animals) are slower to learn to "approach a stimulus to avoid punishment" and "avoid a stimulus to earn reward", relative to "approach to win" and "avoid to avoid punishment" contingencies (Guitart-Masip et al., 2011; Huys et al., 2011). Pre-existing computational models also enable the estimation of Pavlovian bias strength and other cognitive parameters such as learning rate and reward sensitivity. The model we implement—an adaptation of a Q-learning model—is also well integrated with broader cognitive and neural frameworks (Albrecht et al., 2016; Cavanagh et al., 2013; Guitart-Masip et al., 2011; Huys et al., 2011; Mkrtchian et al., 2017; Raab & Hartley, 2020).

Previous work using this paradigm (Mkrtchian et al., 2017) found that the Pavlovian punishment suppression bias parameter was exaggerated in participants with severe mood and anxiety disorders relative to healthy controls. These findings are expected given reports that instrumental performance of individuals with depression is impaired following negative feedback (Dombrovski et al., 2015) and in contexts characterised by frequent punishments (Vandendriessche et al., 2023). This pattern of results however was not replicated in a subsequent study using the cued go-no/go task, with clinically depressed outpatients showing similar model parameters as healthy controls (Moutoussis et al., 2018).

To further investigate this issue of mixed results, we examined the interaction between instrumental and Pavlovian learning and the interaction with depressive symptomatology in a sub-clinical population of young adults. By using a large, relatively homogenous sample (participants of a similar age and education level), we can partially control for additional extraneous factors which influence learning (e.g., age and education), in turn increasing our sensitivity to differences in learning as a function of depression. Ultimately, a better understanding of Pavlovian biases, particularly punishment suppression, in sub-clinical depression could lead to novel interventions aimed at reducing behavioural inhibition in those at risk from developing a depressive disorder (see e.g., Ereira et al., 2021; Fleming et al., 2023).

In the current pre-registered study (pre-registration link: https://osf.io/tqwjd) we hypothesised that individuals with higher depression scores would be more sensitive to stimuli signalling potential punishment, in line with theoretical models (Gotlib & Joormann, 2010; Keren et al., 2018; Kircanski et al., 2012; LeMoult & Gotlib, 2019) and previous findings using other reinforcement learning tasks (Dombrovski et al., 2015; Vandendriessche et al., 2023; review: Pike & Robinson, 2022). Specifically, we expected that response suppression induced by stimuli signalling potential punishment would be exaggerated in those with higher depression scores. This Pavlovian suppression would interfere with instrumental responding, specifically on incongruent go-to-avoid-punishment trials (where participants had to learn to make an instrumental go response and errors were punished with loss of points). We also pre-registered analyses examining the correlation between depression scores and behavioural parameters (punishment suppression bias, reward invigoration bias). Finally, as an exploratory analysis we fit a computational model using previously established methods (Albrecht et al., 2016; Cavanagh et al., 2013; Mkrtchian et al., 2017; Raab & Hartley, 2020) to assess whether key model parameters such as learning rate and Pavlovian bias (the tendency for behavioural activation or inhibition in the presence of reward and punishment, respectively) correlated positively with DASS depression scores.

2. Method

2.1. Participants

All participants were first year psychology students at UNSW Sydney and earned course credit for their participation. Participants also earned points during the task and those who scored in the top 20 % received a $15 voucher from a store of their choice. The experiment was run twice, to probe reproducibility of key findings.

In Experiment 1, 97 participants completed the study with two participants excluded for poor performance (see results section). Of the remaining 95 participants, 55 were female, 39 were male, and 1 identified as other (not specified); mean age: 19.7 years, SD: 4.4 years. In Experiment 2, 82 participants completed the study, with eight performance exclusions. Of the remaining 74 participants, 51 were female, 21 male, 2 identified as other (not specified); mean age: 19.4 years, SD: 2.1 years. The experiments were run approximately one year apart (Experiment 1: July – September 2021, Experiment 2: September – October 2022). All participants were first-year UNSW Psychology undergraduate students, with similar demographic profiles. Participants in the two Experiments did not differ significantly in terms of age, $t(167) = 0.51$, $p = 0.611$, $d = 0.08$, nor gender distribution, $X^2(3) = 4$, $p = 0.261$.

A post-hoc G*Power analysis for repeated measures ANOVA suggested that 80 participants would give 80 % power to detect a small effect size ($f = 0.012$) for the interaction between within-subject variables (four levels) and between-subject variables (modelled for convenience as 2 groups: high vs. low depression). Furthermore, 80 participants would give 80 % power to detect a medium-size correlation ($r = 0.27$) between depression scores and task parameters.

2.2. Materials

2.2.1. Reinforcement learning task

During the task participants had to learn the correct response (Go vs. No-Go) for four cartoon monsters via trial and error. One monster appeared on each trial, and participants had to either click on the monster ("Go" response) or refrain from clicking ("No-Go" response; see Fig. 1). Two of the monsters were associated with earning points (a correct response would earn 100 points, and incorrect responses resulted in no change) while the other two monsters were associated with losing points (a correct response would not earn any points, but an incorrect response would result in the loss of 100 points).

Action and valence were crossed orthogonally so that for one monster in either the "winning" or "losing" category, the correct response was to approach by clicking (go), while for the other monster in that category the correct response was to not click (no-go). This created two congruent conditions: "Go-to-Win" (approaching potential rewards) and "No-Go-to-Avoid-Losing" (avoiding potential losses). There were also two incongruent conditions: "Go-to-Avoid-Losing" (approaching despite the risk of loss) and "No-Go-to-Win" (avoiding despite potential reward). In the congruent conditions, participants' Pavlovian reflexes align with and facilitate the instrumental response (e.g., in the "Go-to-Win" condition, approaching the reward-signalling monster was also the correct instrumental action to obtain reward). In the incongruent conditions, however, Pavlovian responses interfere with the learning process (e.g., in the "No-Go-to-Win" condition, participants had to override their instinct to approach and not respond to earn the reward). The monster-condition association was randomised between participants as to avoid any stimuli specific effects.

Each trial had two phases: the stimulus presentation phase and the feedback phase (see Fig. 2B). Participants were first shown one of four monsters and needed to decide whether to click on the monster (Go) or refrain from clicking (No-Go). The monster appeared randomly within one of the four quadrants of the screen. After 2500 ms (or immediately following a response) the monster vanished and reward feedback was presented, showing either "+100 POINTS," "-100 POINTS," or "0 POINTS." This feedback remained on screen for 1200 ms. A random intertrial interval followed, lasting either 800 ms, 900 ms, or 1000 ms.

Participants had to learn the correct response (Go or No-Go) for each monster via trial and error. Feedback was probabilistic and invalid on 20 % of the trials (e.g., despite making the correct response participants received feedback suggesting they had made an error) making the learning process non-trivial.

Each block comprised 40 trials, consisting of five mini blocks of eight trials in which each of the four monsters were shown twice in a randomised order.

2.2.2. Depression and anxiety stress scale (DASS)

To assess depressive symptoms, participants completed the depression subscale of the Depression, Anxiety, and Stress Scale (DASS-21; Lovibond & Lovibond, 1995). The DASS-21 is a brief 21-item self-report questionnaire, with seven items specifically related to depression. Example items include: "I couldn't seem to experience any positive feelings at all" and "I felt that I had lost interest in just about everything.". Participants are asked to rate the degree to which the statements applied to them over the past week on a scale ranging from 0 = "did not apply to me at all" and 3 = "applied to me very much, or most of the time." Depression scores on the DASS-21 can range from 0 to 21, and these scores were subsequently doubled to align with the 42-item version of the DASS. Research has indicated that the DASS is a reliable measure of depression, with high internal consistency ($\alpha = 0.89$) for the depression subscale in young Australian samples, and strong construct validity (Mellor et al., 2015).

2.2.3. Procedure

The task was programmed in Inquisit (Inquisit 5, 2016). Participants registered for the study through the UNSW online research participation portal and completed the study online in their own time. In the first Experiment (but not Experiment 2), participants first completed an approach avoidance task (data not shown) before completing the reinforcement learning task. The approach avoidance task lasted approximately 10 min and involved looking at images of people being active (e.g., exercising, carrying heavy bags) vs. not active (sitting at a desk, watching TV). Participants had to respond to the orientation of the image (portrait or landscape) by moving the cursor either to the top of the image ('avoid') or the bottom of the image ('approach').

At the beginning of the reinforcement learning task, participants were told that the aim was to collect as many points as possible and at

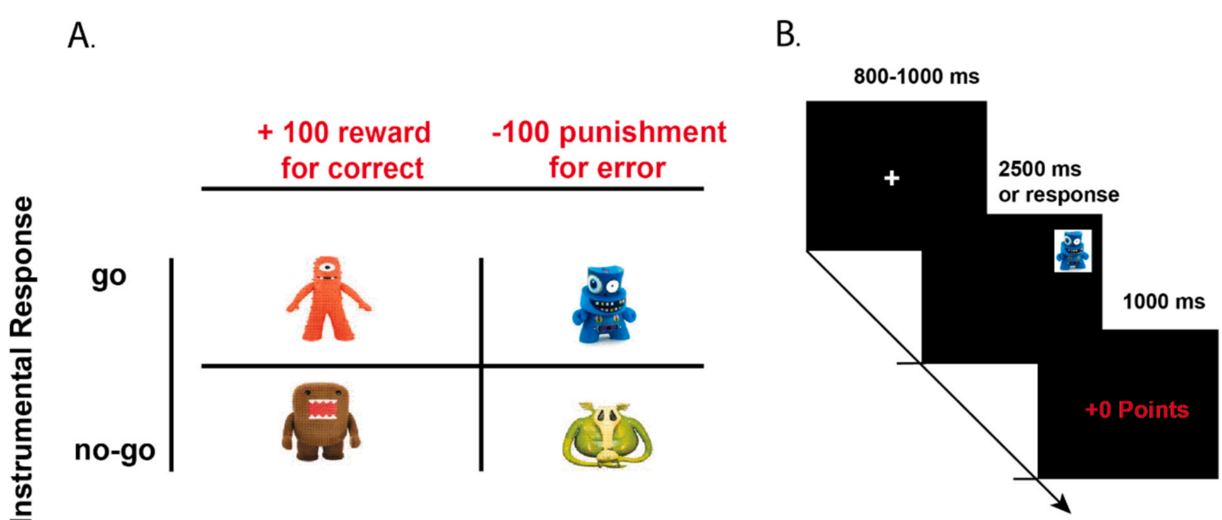

Fig. 1. Reinforcement Learning Task: stimuli and trial structure. *Note.* A. Across four different monster stimuli, action (Go/No-Go) was crossed orthogonally with valence (reward/punishment). Participants learned by trial and error which response (Go or No-Go) is correct for each monster. Incongruent conditions (Go-to-avoid-punishment and No-Go-to-earn-reward) are typically more difficult to learn. B. On each trial a monster could appear at any of the four quadrants. Participants had to make a go response or wait for the monster to disappear. Feedback was either +100 points, +0 points, −100 points.

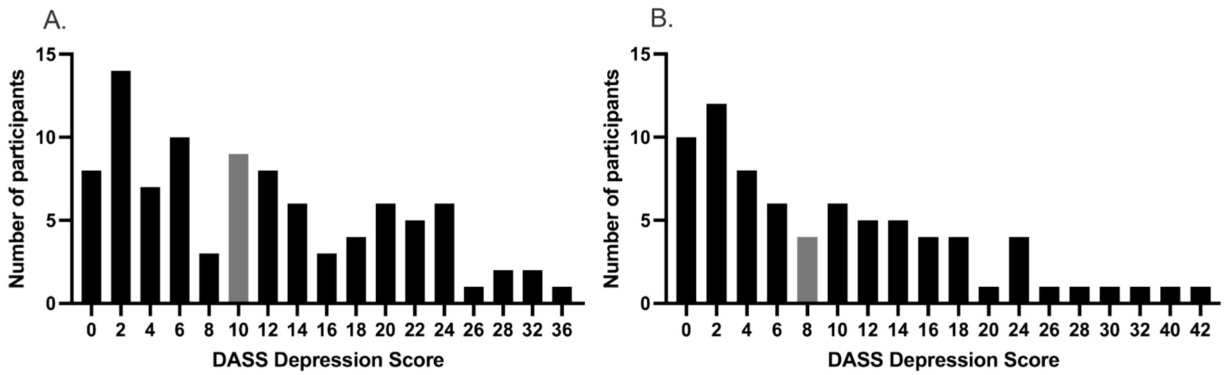

Fig. 2. Distribution of DASS Depression Scores for Experiment 1 (A) and Experiment 2 (B) Note. Scores on the DASS Depression subscale can range from 0 to 42. Scores of 10–13 indicate mild depression, 14–20 moderate, 21–27 severe and 28+ extremely severe. The median is indicated by the grey bar.(Notably, two participants scored in the top percentiles for DASS depression in Experiment 2 (Crawford et al., 2011). It is likely that these participants were not completing the questionnaire accurately. However, we did not plan to use DASS score as exclusion criteria so these participants remain in the analysis. We note however that even if these two participants with extreme DASS scores are excluded, the pattern of results does not change.).

the end of the task, the top-20 % of participants would earn a $15 from a store of their choosing. Participants were then guided through 16 practice trials to ensure they understood the task. The practice trials were similar to the actual task, but two different monsters were used (one where the correct response was to click and one where the correct response was not to click) and the trials progressed at a slower speed than the real task. Participants then completed four blocks of 40 trials of the real task, with a self-paced break in between each block. On completion, participants were informed of the total points they had earned and then filled-out the DASS depression scale and demographic questionnaire.

2.3. Data analyses

Analysis procedures for the behavioural data were preregistered at https://osf.io/tqwjd. Mean accuracy was first computed across the entire task and participants who scored less than 50 % were removed from all subsequent analyses (see Participants section for number). Mean accuracy level across the four trial types was calculated for each participant and entered into a 2 × 2 repeated measures ANCOVA with factors instrumental action (Go vs. No-Go) and congruency (congruent vs. incongruent). The centred DASS depression scores were entered as a covariate. As pre-registered, a median split approach was used to follow up significant interaction effects involving the DASS depression score.

As pre-registered, two behavioural bias scores were calculated: a reward-invigoration bias score (TotalGoResponsesWinTrials/TotalGoResponses) and a punishment-suppression score (TotalNoGo ResponsesPunishmentTrials/TotalNoGoresponses). Perfect performance, where Pavlovian biases did not interfere with carrying out the instrumental response would give a bias score of 0.5 with scores greater than 0.5 indicating either an approach bias or an avoidance bias, respectively. These bias scores were then correlated with the depression score.

2.4. Computational modelling

The details of the computational modelling analyses were not pre-registered but followed previously established methods (Albrecht et al., 2016; Cavanagh et al., 2013; Mkrtchian et al., 2017; Moutoussis et al., 2018; Raab & Hartley, 2020) which used the same experimental paradigm.

We detail a full 6-parameter reinforcement learning model below. We compared models across the full model space, using all possible parameter combinations, to determine the best fitting model before pursuing further analyses. Previous studies used a hierarchical fitting approach, however applying the established fitting procedure (Albrecht et al., 2016; Cavanagh et al., 2013; Moutoussis et al., 2018) to the current data resulted in convergence issues when fitting the full hierarchical model, that were not solved by centering the priors definitions or by constraining the priors. We therefore opted for a non-hierarchical approach that we detail after the model description.

The Q-learning model assumes participants estimate a Q-value for each state-action pair and update these Q-values according to the experienced outcomes. In our task an action is either Go or No-Go and a state refers to one of the four possible monsters (see Methods).

$$Q_t(a_t, s_t) = Q_{t-1}(a_t, s_t) + \alpha(\rho r_t - Q_{t-1}(a_t, s_t)) \quad (1)$$

where r_t is the reward received at time t, either 0 or 1. The sensitivity to the reward received is scaled by ρ, which is further split into ρ_{reward} *and* $\rho_{punishment}$ and was constrained between 0 and 100. α is the learning rate, constrained between 0 and 1. State-action estimates are then weighted by a go-bias, b, which scales an individual's propensity to "go":

$$W_t(a, s) = \begin{cases} Q_t(a, s) + b & \text{if } a = go \\ Q_t(a, s) & else \end{cases} \quad (2)$$

Similarly, a Pavlovian Bias term (constrained between 0 and 100), π, scales the value of a particular state, $V_t(s)$ as follows:

$$W_t(a, s) = \begin{cases} Q_t(a, s) + b + \pi V(s) & \text{if } a = go \\ Q_t(a, s) & else \end{cases} \quad (3)$$

$$V_t(s_t) = V_{t-1}(s_t) + \alpha(\rho r_t - V_{t-1}(s_t)) \quad (4)$$

The intuition behind the Pavlovian bias term, π, is that it increases the propensity to "Go" for states which result in reward and inhibits "Go" responses for states associated with punishment.

Choice is determined by a softmax function which gives the probability of an individual making a "Go" action for a given state:

$$p(go_t, s_t) = \frac{\exp(W(go_t|s_t))}{\exp(W(go_t|s_t) + \exp(W(nogo_t|s_t))} \quad (5)$$

The probability of a Go action is also affected by an irreducible noise parameter, ξ, which estimates inattention during the task and was constrained between 0 and 1:

$$p(go_t, s_t) = \xi(p(go_t, s_t)) + \frac{1-\xi}{2} \quad (6)$$

Models were fit to the data from each individual using Stan in *R*. We note that previous studies fit the model hierarchically, but we observed model degeneracies (i.e., numerous divergent transitions, high R hat values, and low effective sample sizes) for the most complicated models (those with five or more parameters) when fitting hierarchically.[1] We opted to instead fit data to the models in a non-hierarchical manner; this approach yielded convergence across models for all participants (e.g., all mean R-hat values <1.005 for all parameters; all maximum R-hat values <1.12 for all parameters). Further details on model fits, such as parameter priors and convergence metrics can be viewed in the Supplementary Materials.

In addition, we report the results of a hierarchical model which has four parameters—Rho (single parameter for reward and punishment), alpha (learning), Pavlovian bias, and Go bias—that successfully converged in the Supplementary Materials (Section 3). We also provide a more extensive explanation of the approaches we took to resolve degeneracies in the full Hierarchical model.

Individual model fits were performed separately for each subject and used 4 chains with 5000 iterations each, 1000 of which were discarded as burn in. Once all models were fit for each subject in Experiment 1, we compared model fit at the subject level using Leave One Out Cross Validation (LOO-CV) and for each subject found the model with the lowest information criteria (LOO-IC). We then ranked models according to how many subjects the model was selected as best, second-best, and so on. According to this criterion, the best model was the full 6-parameter model described above, which was selected as the best model for 25 participants in Experiment 1. The next best model was the full model without the noise parameter, which was the best model for 16 participants in Experiment 1. The third best model was a model containing a single Rho value, alpha, Pavlovian bias and go bias terms, which was the best fit for 12 subjects. In the results section we therefore detail the parameter estimates and subsequent analysis for the full model for both Experiments 1 and 2.

All code and model fits can be accessed here: https://osf.io/yg9b6/. See the Supplementary Materials for further details.

3. Results

3.1. Participant characteristics

As pre-registered, two participants with overall accuracy of less than 50% were excluded from Experiment 1, leaving a total sample of 95. Eight participants were subsequently excluded from Experiment 2, leaving a total sample of 74. Fig. 2 shows the distribution of DASS depression scores across the two samples. When comparing across experiments, the two samples did not differ significantly in terms of mean depression scores, t (167) = 1.0, p = 0.318, d = 0.15. Although the median DASS depression score for Experiment 1 was in the clinical range (mild depression: see Fig. 2), Mann-Whitney U test suggested that this was not significantly higher than the (non-clinical) median for Experiment 2, U = 3089, p = 0.175. Participants in the two experiments also did not differ significantly in overall accuracy on the reinforcement learning task, t (167) = 0.01, p = 0.992, d < 0.01.

3.2. Preregistered analyses

Experiment 1: The ANCOVA on accuracy found that participants were, on average, more accurate for congruent trials (i.e., where the Pavlovian response and instrumental action aligned), relative to incongruent trials (where action tendencies were competing with one another): main effect of congruence, $F(1,93) = 61.81$, $p < 0.001$, $\eta_p^2 = 0.4$. The main effect of instrumental action (go vs. no-go) was not significant, $F(1,93) = 1.07$, $p = 0.305$, $\eta_p^2 = 0.01$ but there was a significant interaction between depression scores and instrumental action, $F(1,93) = 5.374$, $p < 0.023$, $PES = 0.06$. Follow-up t-tests (median split on DASS depression) indicated that individuals scoring higher in depression symptoms were more accurate (mean proportion correct 0.83 *SEM*: 0.02) on no-go trials, compared to those with lower depression scores (mean proportion correct 0.75 *SEM*: 0.03), $t(93) = 2.5$, $p = 0.016$, $d = 0.49$ (see Fig. 3A), suggesting an increased tendency to withhold responding, regardless of the signalled outcome. No significant difference between depression groups was observed for accuracy on go trials overall, $t(93) = 1.3p = 0.189$, $d = 0.28$, although numerically individuals with higher depression scores responded less frequently. Contrary to our hypotheses there was no significant difference between depression groups on the go-to-avoid-punishment trials, $t(93) = 0.98$, $p = 0.166$ (one-sided), $d = 0.2$. All other interaction effects, and the main effect of DASS depression score, were not significant in the ANCOVA, $Fs < 3.02$, $ps > 0.086$, $\eta_p^2 < 0.03$.

Experiment 2: Results of the ANCOVA can be seen in Fig. 3B. As in Experiment 1, participants were more accurate on congruent trials where the Pavlovian response and instrumental action aligned, relative to incongruent trials where these action tendencies were competing with one another: main effect of congruence, $F(1,72) = 29.0$, $p < 0.001$, $\eta_p^2 = 0.287$. The main effect of instrumental action (go vs. no-go) was significant, $F(1,72) = 24.47$, $p < 0.001$, $\eta_p^2 = 0.254$, but superseded by a significant interaction between these two variables, $F(1,72) = 12.04$, $p = 0.001$, $\eta_p^2 = 0.14$. Participants were more accurate on go relative to no-go trials (see Fig. 3B), which was particularly pronounced for congruent trials. There was no significant main effect nor interactions involving depression scores, $Fs < 1$, $ps > 0.526$, $\eta_p^2 < 0.0076$.

In both experiments the mean reward invigoration bias was significantly greater than 0.5, Experiment 1: *M:* 0.56 *SEM:* 0.008, one sample $t(94) = 7.6$, $p < 0.001$, $d = 0.78$. Experiment 2: *M:* 0.55, *SEM:* 0.009, $t(73) = 5.22$, $p < 0.001$, $d = 0.61$. However, there was no significant correlation with DASS depression score in either experiment, $rhos < -0.13$, $ps > 0.209$. Similarly, the mean punishment suppression bias was significantly greater than 0.5, Experiment 1: *M:* 0.58 *SEM:* 0.012, one sample $t(94) = 6.5$, $p < 0.001$, $d = 0.67$. Experiment 2: *M:* 0.57, *SEM:* 0.012, $t(73) = 5.50$, $p < 0.001$, $d = 0.640$. No correlations were observed with DASS depression score, $rhos < .07$, $ps > 0.556$.

3.3. Exploratory Bayesian ANCOVA combined datasets

We used jamovi with default (uninformative) priors (Jamovi Project, 2021) to run an exploratory Bayesian ANCOVA, combining data from all 169 participants. To isolate the strength of evidence for the main effects and interaction terms within the Bayesian ANOVA models we used the ‘effects across matched models’ approach (Mathôt, 2017; van den Bergh et al., 2019). This procedure involves comparing models that contain the effect to equivalent models that are stripped of the effect. Data and Output from jamovi can be found at https://osf.io/yg9b6/.

Accuracy was examined in a model with within subject factors of instrumental action (Go vs. No-Go) and congruency (congruent vs. incongruent). Experiment was entered as a between-subjects factor and DASS depression scores entered as a covariate. Model terms included all main effects as well as interactions between instrumental action and congruence, depression scores and congruence, depression scores and instrumental action and the three way interaction between these variables. Relative to the null model (that included only subject), the strongest alternative model included instrumental action, congruence and their interaction, $BF_M = 19.6$. The strength of the evidence for this model over the null model was conclusive, $BF_{10} = 2.18e+16$, error % =

[1] Numerous attempts were made to improve the model fit, such as: restricting (and relaxing) priors, non-centering the model, removing the exponentiation of transformed parameters, running on a smaller subset of participants, adjusting both maximum tree-depth and adapt delta. The only approach which led to model convergence was removing the maximum value restrictions on the Rho-reward and Rho-punishment parameters (which are otherwise restricted between 0 and 100). The issue with this solution, however, is that the subsequent posterior estimates ranged between 0 and 1 billion, with flow on consequences for the other estimated parameters. For these reasons we have reported the non-hierarchical full model in the main text and report the results of the hierarchical four parameter model in the supplementary.

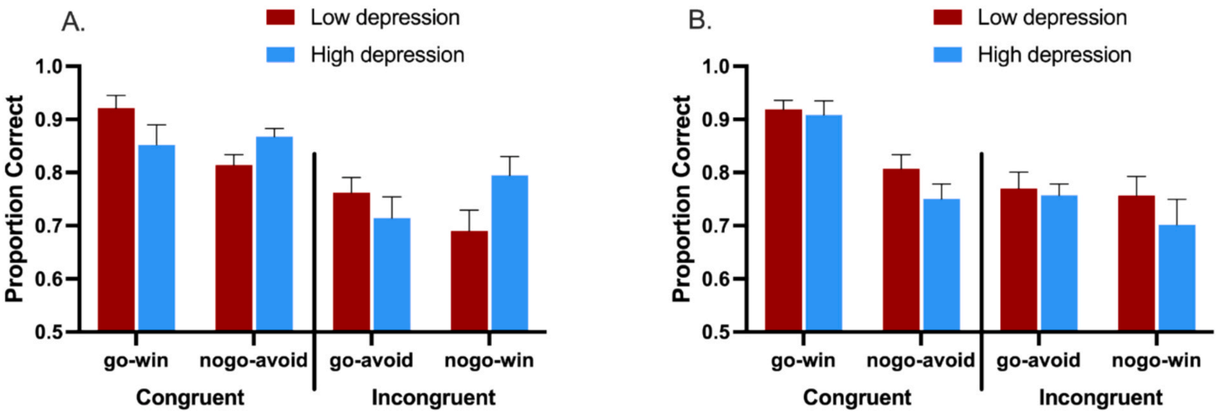

Fig. 3. Accuracy across the four trial types in Experiment 1 (A) and Experiment 2 (B) as a function of depression score (median split for visualisation purposes) *Note.* Mean accuracy on congruent trials where the Pavlovian and instrumental actions aligned (go-to-win and no-go-to-avoid-losing) and incongruent trials where these action tendencies were in conflict (go-to-avoid-losing and no-go-to-win). DASS depression score was entered as a covariate in the analysis, but median split data shown here for convenience. Error bars show *SEM*.

2.9. The only other viable model included these three factors in addition to DASS depression and the interaction between depression score and instrumental action, $BF_M = 13.4$, with $BF_{10} = 1.67e + 16$, error % = 5.2. Moderate evidence was found favouring exclusion for main effects of experiment, $BF_{inclusion} = 0.148$ and depression, $BF_{inclusion} = 0.159$, exclusion of the interaction between DASS depression and congruence, $BF_{inclusion} = 0.168$, and exclusion of the three-way interaction $BF_{inclusion} = 0.182$.

To further investigate the interaction between instrumental action and depression score we used Bayesian paired-sample t-tests (2-tailed) to compare mean accuracy on go vs. no-go trials separately for the 82 participants scoring less than the median of 10 vs. the 87 participants scoring 10 or more on the DASS depression scale. Participants with lower levels of depression were more accurate on go trials (*M*: 84 %, *SEM*: 2 %), vs. no-go trials (*M*: 77 %, *SEM*: 2 %), $BF_{10} = 28.9$. By contrast, participants scoring higher in depression performed similarly for both go trials (*M*: 82 %, *SEM*: 2 %) and no-go trials (*M*: 79 %, *SEM*: 2 %), with moderate evidence for the null, $BF_0 = 4.5$.

3.4. Computational modelling analyses

After determining that the full model provided the best fit (i.e., lowest LOO-IC across the greatest number of subjects) we assessed whether the mean of the posterior parameter estimates—primarily the alpha learning rate, Pavlovian bias, and reward sensitivity parameters—correlated with individual's DASS depression scores. While the behavioural data showed little relationship between task behaviours and DASS scores, recovery of latent variables that may support behaviour, as yielded by computational modelling, may offer greater sensitivity for determining whether Pavlovian biases influence reinforcement learning differentially as a function of depression symptomatology—as has been suggested by observations of relationships between parameter values and depressive symptom levels in previous work (Dombrovski et al., 2015; Mkrtchian et al., 2017; Vandendriessche et al., 2023).

To this end, we took the means of the posterior estimates for each individual, for each parameter, and assessed their relationship to DASS depression scores via multiple individual linear regressions. We checked variables for collinearity (Fig. 4). Correlations for some parameters, particularly in Experiment 2, were non-negligible (above 0.3). We therefore opted to use multiple individual linear regressions in order to avoid issues of collinearity and to keep the dependent variable as the parameter itself—as depression values plausibly affect parameter values, yet parameter values are unlikely to cause symptoms of depression. While the regression analysis was exploratory, we reasoned we could assess the robustness of any observed relationships by checking whether an analogous effect was observed in Experiment 2, and vice

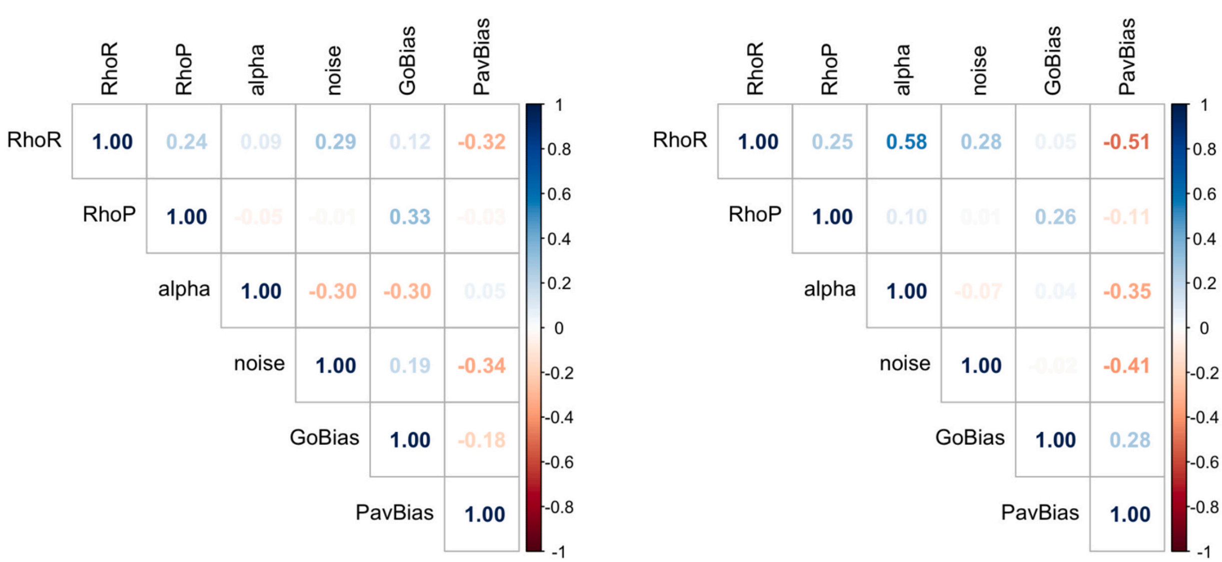

Fig. 4. Collinearity measured by R-values between model parameters for Experiment 1 (left panel) and Experiment 2 (right panel).

versa.

To summarise the results, we did not observe any *reliable* relationships between parameter estimates and individual depression scores; any relationships which did arise (e.g., learning rate and depression in Experiment 1) did not replicate across experiments. A summary of participants' average posterior parameter estimates (means and standard deviations) for both Experiments 1 and 2 can be seen below in Table 1. A correlation matrix for the relationships between these posterior parameter estimates and participants' DASS depressions scores is summarised in Table 2.

It is also worth noting that no reliable relationships were observed between the posterior parameter estimates obtained via the four parameter hierarchical model and the DASS scores. The results from this analysis are reported in the Supplementary Materials along with the convergence metrics.

4. Discussion

In the current pre-registered experiments, we used the cued go-no/go task to investigate the interference of cues signalling Pavlovian punishment (and reward) on the acquisition of instrumental responding. Furthermore, we investigated whether depressive symptomatology interacted with instrumental learning and the effects of Pavlovian cues.

Using a variety of reinforcement learning tasks, some studies have reported impaired instrumental performance of individuals with depression in contexts featuring frequent punishment or negative feedback (Dombrovski et al., 2015; Vandendriessche et al., 2023; reviews: Chen et al., 2015; Pike & Robinson, 2022) and increased suppression of instrumental responding in the presence of Pavlovian stimuli signalling punishment (Mkrtchian et al., 2017; Nord et al., 2018). These results, however, are often inconsistent (Huys et al., 2016; Moutoussis et al., 2018). To overcome common hurdles inherent to clinical research (e.g., small sample sizes, heterogeneity of patient demographics, symptom severity and treatment history) the current study used a large sample of young adults who differed in DASS depression scores but were otherwise largely homogenous.

In line with previous studies which have used this task we found that participants performed better on congruent trials (where Pavlovian and instrumental actions aligned) relative to incongruent trials (where participants needed to override Pavlovian approach and suppression behaviour to carry out the correct instrumental response). The results of Experiment 1 (and the exploratory combined behavioural analysis of all 169 participants) found that individuals who scored higher on the depression scale had better accuracy on no-go trials relative to their less depressed peers—indicating they were less likely to make a 'go' response when it was inappropriate. This improvement in accuracy, in Experiment 1, was reflected by a higher learning rate parameter (alpha) estimates for depressed individuals. Experiment 2 however found no such differences in either people's responses (i.e., depression scores did not correlate with any behavioural response measures) or estimates of the relevant parameters.

These results suggest that if a relationship does exist between subclinical depression and the effect of Pavlovian cues on instrumental

Table 1
Parameter Means Means and standard deviations for the individual posterior parameter estimates.

Parameter	Mean	SD	Mean	SD
	Experiment 1		*Experiment 2*	
$\rho reward$	19.136	16.179	17.898	14.196
$\rho punishment$	12.977	11.9	10.072	9.964
$\alpha(learningrate)$	0.410	0.229	0.308	0.203
$\xi(noise)$	0.929	0.106	0.942	0.090
$b(gobias)$	0.796	1.739	0.717	1.026
$\pi(Pavlovianbias)$	0.472	0.730	0.589	0.650

Table 2
Correlations Estimates and correlation coefficients of relationship between individuals' DASS depression scores and their posterior parameter estimates.

Parameter	Estimate	R^2	*p-value*	Estimate	R^2	*p-value*
	Experiment 1			*Experiment 2*		
$\rho reward$	−0.004	0.002	0.985	0.08	0.027	0.818
$\rho punishment$	−0.059	0.045	0.669	−0.025	0.012	0.920
$\alpha(learningrate)$	0.007	0.278	0.007**	0.000	0.004	0.972
$\xi(noise)$	−0.001	0.075	0.473	0.002	0.126	0.286
$b(gobias)$	−0.036	0.187	0.072	0.013	0.062	0.600
$\pi(Pavlovianbias)$	0.008	0.098	0.347	−0.005	0.040	0.737

Note. P-values are uncorrected. The only statistically significant relationship (i.e., learning rate with depression scores) in Experiment 1 was repudiated by the data in Experiment 2.

responding, then such a relationship is not easily observed in environments such as the cued go/no-go task. It is also worth noting that while there is empirical evidence suggestive of a relationship between depressive symptoms and instrumental learning, these observations have often been inconsistent (see e.g., Brown et al., 2021; Cavanagh et al., 2019; Chase et al., 2010) similar to the inconsistencies observed here. One possible explanation for this inconsistency is the limited test–retest reliability of the reinforcement learning task, which may make it ill-suited for research focused on individual differences. Many behavioural tasks, especially those that assess differences in performance across conditions, are known to suffer from poor test–retest reliability (Edwards et al., 2024; Green et al., 2016; Pronk et al., 2022). This issue is often attributed to low between-subject variability in such tasks which means that they are effective for detecting robust experimental effects at the group level but lack the precision for individual-level analyses (Hedge et al., 2018). This is problematic in fields such as computational psychiatry, and some sub-disciplines of psychology, where researchers wish to correlate task parameters with scores on questionnaire measures. A recent analysis using a reinforcement learning task, similar to that used in the current experiments, reported poor test–retest reliability for both behavioural measures and computational parameters over a space of five weeks (Palminteri et al., 2025). We could not assess test–retest reliability here (for example, by using splitting methods within single-session data) because learning parameters naturally evolve during the reinforcement learning task. However, poor test–retest reliability may explain the inconsistent results between task parameters and depression scores seen across Experiments 1 and 2.

Another possible explanation for this inconsistency is that the relationship between learning and depression is context based. Vandendriessche et al. (2023) find that depressed patients differ from healthy controls when the context is negatively valenced (i.e., the expected outcome is negative), yet observe no differences in positive domains. This finding however does not explain our current results given there is no difference in accuracy, as function of depression, between the punishment trials and reward trials.

A more likely scenario is that the depressive states of the subjects used (i.e., a sub-clinical population) are not strong enough to elicit the obscuring effects of anhedonia on learning. While we chose this sample in order to control for other extraneous variables which may influence learning, this is only beneficial if sub-clinical levels of depression still result in behavioural differences. It is also worth noting that while our samples exhibited a range of depression scores, it is unclear whether all participants used the DASS as intended; two participants in Experiment 2 reported scores in the top possible range, with one participant reporting the highest possible score on the DASS. Given these students with exceedingly high scores were enrolled and participating at university, we believe it is more likely that they did not take the questionnaire seriously, rather than them currently experiencing severe depressive episodes. Although this was not a pre-registered exclusion critiera, we note that removing these two extreme DASS values from the analyses does not change the pattern of results in Experiment 2. A further limitation affecting interpretation across experiments is the fact that participants in Experiment 1 performed a short approach avoidance task before the reinforcement learning task, whereas participants in Experiment 2 did not. Although it seems unlikely, we cannot rule out the possibility that performing this task affected their subsequent performance in the reinforcement learning task.

Relatedly, it could be theorised that participants with sub-clinical depression need to be in negative emotional states the task in order to capture sensitivity to signalled punishment. However, a recent study which used a large sample of young adults found no effect of mood induction on people's learning and subsequent behaviours in a Go-NoGo paradigm comparable to that employed here (Weber et al., 2022). Similarly, they also found no evidence that individual differences in depression and hypomania were related to the degree to which the mood induction affected performance.

Together these studies suggest that while Go-NoGo paradigms are an excellent tool to study the interference from Pavlovian approach and suppression responses on instrumental actions, potential cognitive biases in reinforcement learning are not always clearly related to symptoms of sub-clinical depression. These results are disappointing, as a clear signature of potentially pathological Pavlovian punishment biases in young adults could lead to a better mechanistic understanding of depression risk and potential for novel interventions aimed towards sub-clinical populations (Ereira et al., 2021; Fleming et al., 2023). These results are nonetheless informative as they show that if a reliable moderating effect of depression on learning exists, especially in contexts where Pavlovian and instrumental responses collide, then these effects may only be observable in clinical populations.

From a *meta*-science perspective, our inconsistent results are a reminder for the field that a reliance on single studies, whether adequately powered or not, can lead to erroneous conclusions; in our case, if we were to have proceeded without running Experiment 2, we would've formed the (potentially false) belief that depression is associated leads to relatively large differences in learning rates. Our use of computational modelling and subsequent model comparison also shows the significant heterogeneity present in people's response patterns in such tasks and the caution required in attributing any one model as being indicative of the underlying computational processes involved in a decision.

CRediT authorship contribution statement

Jake R. Embrey: Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Data curation. **Kelly G. Garner:** Writing – review & editing, Validation, Supervision, Investigation, Formal analysis. **Julyani Salim:** Writing – review & editing, Methodology, Investigation, Data curation, Conceptualization. **Poppy Watson:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors are grateful to Matthew Albrecht for his advice on the computational modelling aspect of this study.

Funding

This study was funded by an Australian Research Council Early Career Fellowship (No. DE200100591) awarded to Poppy Watson.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.nlm.2025.108092.

Data availability

All data can be accessed at https://osf.io/yg9b6/

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